Community, Work & Family

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/ccwf20

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To cite this article: Ann Bartel, Maya Rossin-Slater, Christopher Ruhm, Meredith Slopen & Jane Waldfogel (2023): The impact of paid family leave on employers: evidence from New York, Community, Work & Family, DOI: 10.1080/13668803.2023.2168516

To link to this article: https://doi.org/10.1080/13668803.2023.2168516

COMMUNITY, WORK & FAMILY
https://doi.org/10.1080/13668803.2023.2168516

Routledge
Taylor & Francis Group

RESEARCH ARTICLE

The impact of paid family leave on employers: evidence from New York

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ABSTRACT

To study the impacts of New York's 2018 Paid Family Leave (PFL) policy on employer outcomes, we designed and fielded a survey of small firms in New York and a control state, Pennsylvania, which does not have a PFL policy. We match each NY firm to a comparable PA firm and use difference-in-differences models to analyze within-match-pair changes in outcomes. Contrary to common concerns about the burdens of PFL on employers, we find no evidence that PFL had any adverse impacts on employer ratings of employee performance or their ease of handling long employee absences. Instead, we find suggestive evidence of an improvement in employers' ratings of employee commitment and cooperation, concentrated in the first policy year. We also observe an increase in employers' ratings of the ease of handling employee absences in the first policy year. Lastly, we find a rise in the incidence of employee leave-taking in the second policy year, driven by the smallest firms in our study.

ARTICLE HISTORY
Received 14 September 2022
Accepted 10 January 2023

KEYWORDS
Paid family leave; employers; employer surveys; employer attitudes; worker absences

Introduction

The vast majority of Americans are supportive of Paid Family Leave (PFL), a policy that provides workers with paid time off while they care for newborn children or seriously ill family members (Ferrante, 2020). Yet the United States remains the only high-income country without a national paid parental leave policy (OECD, 2021), and only 11 states (CA, CT, DE, OR, MA, MD, NJ, NY, OR, RI, WA) and Washington, D.C., have passed PFL legislation, with four of these having not yet implemented their programs (CO, CT, MD, DE) (National Partnership for Women and Families, 2021). Although the economic and health benefits of PFL for workers and their families have been documented in an expansive literature (see Bartel et al., 2023; Olivetti & Petrongolo, 2017; Rossin-Slater, 2018; Rossin-Slater & Stearns, 2020; Rossin-Slater & Uniat, 2019 for some overviews), the lack of policy action in the U.S. partially reflects concerns about the potential burden that PFL imposes on employers. While most federal PFL proposals and nearly all current state-level policies use employee payroll taxes as financing mechanisms, employers – especially small

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/13668803.2023.2168516.

ones – may face other costs and challenges associated with having to manage their workers' absences (e.g. coordinating work schedules, having to hire replacement workers).[1]

Thus, evidence on the impacts of PFL on employers is necessary to inform the policy debate, but this research has been limited. Existing survey and administrative data sets do not contain information about employers' experiences with managing employee absences, which are key to understanding the potential burden of PFL on firms. Recent studies using administrative data from California and Rhode Island have examined the impacts of paid leave policies in these two states on a range of outcomes for workers and their families, but not employers (Bana et al., 2020; Campbell et al., 2017).

A study using California administrative data shows that firms play an important role in determining the take-up of leave benefits, but does not shed light on the impacts of the program on employer outcomes (Bana et al., 2018). Relatedly, Kamal et al. use data from the U.S. Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) and analyze the impact of a negative labor demand shock on employee composition for firms that are and are not covered by the provisions of the federal Family and Medical Leave Act (Kamal et al., 2020).

Our paper contributes to a small set of studies that have analyzed employers in the context of PFL. Eileen Appelbaum and Ruth Milkman pioneered research on employers with a survey of 250 California firms, which was conducted four to five years after California's first-in-the-nation PFL program was implemented. A central finding from this work is that 90 percent of California employers reported that the PFL policy had either a positive or neutral effect on employee productivity, morale, and costs (Appelbaum & Milkman, 2011; Milkman & Appelbaum, 2013). Another study of 18 employers in New Jersey indicates that businesses do not report adverse impacts of NJ's second-in-the-nation PFL program on profitability or employee productivity (Lerner & Appelbaum, 2014). Most recently, Goodman et al. examine the impacts of San Francisco's Paid Parental Leave Ordinance, which was implemented in 2017 and is the first U.S. policy that mandates that employers provide fully paid leave to workers (Goodman et al., 2020).[2] The authors surveyed employers in San Francisco and surrounding Bay Area counties in 2018, and show that employers report minimal negative impacts and high support for the policy. Overall, this prior research has pointed to minimal negative effects of PFL policies for employers, and suggests the potential for some positive effects.

However, while these studies break new ground in collecting data on employer outcomes, they are limited by a lack of baseline data on pre-PFL outcomes; instead, researchers have asked employers for their assessment of how employee performance has changed as a result of the law. Other limitations of prior research are the absence of control groups that can be followed over time, and the lack of representative samples of firms.

In contrast, Bartel et al. (2016) analyze the impact of Rhode Island's third-in-the-nation PFL program on employers with a survey of small and medium-sized food services and manufacturing businesses in Rhode Island, Connecticut, and Massachusetts. Rather than relying on employer reports of impacts, they collected data on employer outcomes both before and after the program went into effect, and found no statistically significant impacts on a wide range of outcomes. However, small sample sizes generate concerns regarding statistical power to detect meaningful effect sizes, and limit the conclusions that could be drawn from this analysis. Our survey indicates that employers have high ratings on these types of outcomes even in the years *before* the policy, suggesting that pre-PFL data is essential for assessing the impacts that can be attributed to the policy.

Lastly, four recent studies using administrative data from Europe have analyzed the impacts of employee leave-taking on outcomes among employers, with mixed results (Brenøe et al., 2020; Gallen, 2019; Ginja et al., 2020; Huebener et al., 2022). However, the dramatic differences in statutory leave duration, labor market characteristics, and broader policy environments between these European countries and the United States make it challenging to infer lessons from this evidence for the U.S. setting.

New York's Paid Family Leave Act

Before 2018, some workers in New York had access to government-provided job-protected unpaid leave through the federal Family and Medical Leave Act (FMLA) of 1993, which covers workers who meet various eligibility requirements, such as working at an employer with 50 or more employees. In addition, since the 1978 Pregnancy Discrimination Act, birth mothers have been eligible for approximately 6–8 weeks of partially paid disability leave under NY's Temporary Disability Insurance (TDI) program to prepare for and recover from childbirth. TDI provides a wage replacement rate of 50 percent of the average weekly wage for the last 8 weeks worked, but only up to a current (as of 2022) maximum benefit of $170 per week, and the leave is not job protected.[3]

In January 2018, New York state implemented the Paid Family Leave Act (PFLA), thus becoming the fourth state to provide paid leave for new parents and employees caring for a severely ill family member. The program covers all private sector workers and has been implemented gradually over 2018–2021. In 2018, workers were able to claim 8 weeks of job-protected leave with a wage replacement rate equal to 50 percent of the employee's average weekly wage (AWW), up to a maximum benefit set at 50 percent of the state-level AWW. In 2019 and 2020, workers could claim job-protected leave for 10 weeks, with wage replacement rates of 55 and 60 percent of their AWW, up to 55 and 60 percent of the state AWW, respectively. Beginning in 2021, the fully phased-in policy provides 12 job-protected weeks of leave, with 67 percent of the worker's AWW replaced, up to 67 percent of the state AWW (corresponding to a $971.61 maximum weekly benefit). Similar to many other state-level PFL programs, New York's program is funded through a payroll tax on employees.[4]

Data

Survey design

We surveyed a representative sample of firms with 10–99 employees in NY and PA in each fall (September to December) of 2016, 2017, 2018, and 2019. As noted previously, we select our control firms from the state of Pennsylvania, which has a lengthy border with NY and has never had a PFL law.[5]

The survey was approved by the Institutional Review Board (IRB) at Columbia University and conducted by the Office for Survey Research (OSR) at Michigan State University (whose IRB also approved). OSR purchased a sampling frame of eligible businesses in each state from Survey Sampling Inc., a survey research firm specializing in business-based survey research and who maintain a sampling frame of businesses. From this frame, OSR drew random samples within the three firm size and 16 North American Industry Classification System (NAICS) code categories. Thus, within each state, approximately one third of the surveyed employers have 10–19 employees, a third have 20–49 employees, and a third have 50–99 employees.

The initial contact with employers was made by mail, with follow-ups conducted by mail, e-mail, and phone. In each firm, OSR asked either the owner or manager to complete the survey, as these individuals are likely to be knowledgeable about employee performance, the ease of managing employee absences, as well as employee composition and the incidence of employee leave-taking.

In the first survey year (2016), we had a response rate of 46 percent in both states, resulting in a sample of 1,207 firms from each state. Firms were sampled by industry and firm-size strata to ensure that the final sample is representative of the industrial and firm-size composition of the state. In Year 2 (2017), we attempted to re-survey as many firms as possible from the preceding year. We obtained responses from 1,599 of these firms, and recruited 820 new firms to generate a total of 2,419 firms (1,215 from NY and 1,204 from PA), sampling again by industry and firm size to ensure the sample remained representative. We repeated this process in subsequent years, generating a final sample of 4,573 unique firms that participated in the survey in at least one year.

The survey questionnaire covered multiple domains, and is available in Appendix B.

Key outcomes

Employer ratings of employee performance. We asked employers 'On a scale of 1–10, how would you rate your employees in terms of their: (1) attendance; (2) commitment to the job; (3) cooperativeness to get the job done; (4) productivity; and (5) teamwork' (with 1 representing 'very poor' and 10 representing 'excellent'). For each of these 5 dimensions, we generate standardized z-scores by subtracting the analysis sample mean and dividing by the sample standard deviation. Thus, coefficients in regressions that use these outcomes as dependent variables can be interpreted in SD units.

Employer ratings of ease of coordination and handling employee absences. We asked employers 'On a scale of 1–10, how easy or difficult is it for you to: (1) coordinate the work schedules of your employees to ensure the smooth operations of your activities; (2) deal with employee absences of 2 weeks or less; (3) deal with employee absences of between 2 and 4 weeks; and (4) deal with employee absences of 4 or more weeks' (with 1 representing 'very difficult' and 10 representing 'very easy'). For each of these 4 variables, we generate standardized z-scores by subtracting the analysis sample mean and dividing by the sample standard deviation. Thus, coefficients in regressions that use these outcomes as dependent variables can be interpreted in SD units.

Employee leave-taking. We asked employers 'Have you had a female or male employee who took time off work in the past year because they had or adopted a child, or had a family member with a serious illness? (Check all that apply.)'[6] We use the employer responses to create five binary indicator variables: an indicator variable set to 1 for employers who report that any employee has taken any leave for any family-related reason in the past year, and 0 otherwise, as well as separate indicator variables for employers who report having at least one: female employee taking parental leave; male employee taking parental leave; female employee taking leave to care for a seriously ill family member; and male employee taking leave to care for a seriously ill family member.

Independent variables

PFL

Our key independent variable is a binary indicator for the presence of a PFL law. As detailed in the Empirical Analysis section below, we define this based on whether the observation is from NY and from a year when PFL is in effect.

Control variables

Employee attributes. We asked employers about a set of employee attributes. Because paid family leave might be disproportionately valued or used by part-time or female employees, we asked employers how many employees are currently on the payroll, how many work part-time (i.e. less than 35 h per week), and how many are female. We also asked how many employees voluntarily left the firm during the past year, and how many employees were absent for at least one day with no notice or less than 24 h of notice during the past month. We use these responses to construct variables for the share of workers who are female, who work part-time, who quit in the past year, and who were absent without advance notice in the past month as a percentage of employees currently on payroll.

We then use these variables define a set of firm-level control variables measured in the first year the firm is observed in the survey. These variables (and their sample means or percentages) are: number of employees (mean = 36.3); proportion of employees who work part-time (31.6%); proportion female (52.7%); proportion who have worked for the firm for more than one year (85.9%); proportion who quit in the past 12 months (19.8%); and proportion who were absent without advance notice in the past month (9.2%).

Empirical analysis

Our goal is to estimate the causal effect of the NY PFL policy on employer outcomes. We use a difference-in-differences (DD) strategy, comparing the change in outcomes of NY firms to the change in outcomes of control firms, from before to after the policy went into effect. The DD approach relies on an assumption that outcomes in the treatment and control firms would have followed parallel trends in the absence of program implementation. Since we only have two pre-policy years of data (2016 and 2017), we are limited in our ability to comprehensively assess the validity of this assumption by analyzing long pre-treatment trends; however, we do examine changes in outcomes between these two years to obtain some indication of whether such trends exist.

To select our control firms, we use the PA data and select a match for each NY firm using a nearest-neighbor algorithm. We use matching rather than simply using all PA firms in order to improve the comparability of our control group. Our algorithm makes an exact match on industry sector (one of 16 categories) and an indicator for whether the firm is located in a metro area based on the 2013 Rural-Urban Continuum Code

(*Rural-Urban Continuum Codes*, 2020). Then, we conduct a ``fuzzy'' match (with replacement) using the following variables: number of employees in the firm in the first year available in the data, the 2016 county unemployment rate, and the 2016 county average weekly wage. County-level characteristics are obtained from the 2016 Quarterly Census of Employment and Wages (US Bureau of Labor Statistics, 2016). This process yields a sample consisting of a total of 2,364 matched pairs of firms (2,364 NY firms and their 655 PA matches).

Appendix Table A1 reports the means of county-level characteristics used in the matching process. We report the means for all NY and PA firms in the first two columns, and in the NY and PA firms in the matched pair sample in the following two columns. We also report the difference in means of these variables between firms in NY and PA before the match, along with the mean within-match-pair difference after the match. The table shows that the magnitudes of the differences in these variables decline after matching, indicating that the matched firms from PA more closely resemble firms in NY than when using the full sample of PA firms. Appendix Figure A1 depicts the counties in which the NY and PA firms in our matched pair sample are located, with darker colors representing counties with a larger number of firms. As expected, firms in more urban counties in PA (e.g. around Philadelphia) are more likely to be used as matches for NY firms than those in more rural parts of PA.

After constructing our matched pair sample, we estimate DD and event-study models that include match-pair-by-year fixed effects. These models compare changes in the outcomes of NY firms to changes in the outcomes of PA firms within each matched pair. Our DD model takes the following form:

$$Y_{ipst} = \beta_0 + \beta_1 NY_s + \beta_2 Post_t + \beta_3 NY_s x Post_t + \gamma' X_i + \theta_{pt} + \epsilon_{ipst} \tag{1}$$

for each firm *i* in matched pair *p* in state *s* observed in year *t*. NY_s is an indicator for firms located in New York, and $Post_t$ is an indicator set to 1 in the post-implementation years (2018 and 2019). X_i is a vector of baseline firm-level control variables measured in the first year the firm is observed in the survey that includes the number of employees, the proportion of employees who: work part-time, are female, have worked for the firm for more than one year, quit in the past 12 months, and were absent without advanced notice in the past month.[7] Θ_{pt} are interactions between matched pair and survey year fixed effects, allowing us to make comparisons of changes in outcomes within matched pairs of firms. The key coefficient of interest is β_3, which measures the impact of the NY PFL program on the outcome of interest, relative to the change in the matched PA firm over the same time period. To account for the fact a firm can appear multiple times in our data, we cluster standard errors on the firm level.

We also estimate event-study models, which replace the single $Post_t$ indicator in equation (1) with indicators for each survey year (while keeping all of the other variables the same). The interactions between the NY_s indicator and the survey year indicators in these event-study models allow us to examine differential trends in outcomes in NY relative to PA firms, both before and after the law. We omit the 2016×NY interaction term, so the other coefficients measure differential trends relative to the first survey year.

Lastly, since we analyze a large set of outcomes, we address concerns with multiple hypothesis testing by using the Romano-Wolf correction (which also accounts for clustering at the firm level). We report the Romano-Wolf *p*-value associated with our key coefficients of interest for each outcome.[8]

Results

Descriptive statistics

Table 1 reports the means of the key variables in our sample of matched pairs of firms, separately for PA and NY firms, before and after the policy. There are several take-aways from this table. First, average employer ratings of employee performance are consistently high in both states and in all years. In particular, across all five dimensions, and for firms in all categories (PA, NY, pre- and post-policy), the mean rating is higher than 8 on a scale of 1–10. This suggests that there is potentially more scope for observing reductions in performance as opposed to improvements, making any increases in these ratings even more notable.

Second, employer ratings of the ease of coordinating work schedules and dealing with worker absences are considerably lower. Absences longer than four weeks (and to a lesser extent those between two and four weeks) appear to present particular challenges for many employers. Third, although the incidence of leave-taking increases over time in both states, the magnitude of the increase is larger among NY firms.

Main results

Table 2 reports results on the impacts of the NY PFL policy on employer ratings of employee performance. Panel A presents the estimates of the β_3 coefficients from equation (1), while estimates of the coefficients from the event-study models are in

Table 1. Means of key outcome variables, matched pair sample.

	PA Firms		NY Firms	
	Pre	Post	Pre	Post
A. Employer Ratings of Employee Performance				
Attendance	8.11	8.10	8.04	8.09
Commitment	8.12	8.11	8.16	8.27
Cooperation	8.30	8.22	8.28	8.39
Productivity	8.03	8.13	8.13	8.23
Teamwork	8.02	8.16	8.20	8.31
B. Employer Ratings of Ease of Coordination and of Handling Absenses				
Coordination	7.35	7.33	7.31	7.42
Ease of Handling Absences <2 Weeks	6.77	6.52	6.68	6.59
Ease of Handling Absences 2–4 Weeks	5.26	4.67	5.15	4.88
Ease of Handling Absences >4 Weeks	4.39	3.46	4.15	3.72
C. Incidence of Employee Leave in Past 12 Months				
Female Employee – Parental	0.17	0.19	0.14	0.20
Male Employee – Parental	0.13	0.16	0.13	0.15
Female Employee – Serious Family Illness	0.10	0.13	0.12	0.17
Male Employee – Serious Family Illness	0.09	0.12	0.07	0.14
Any Employee Taking Leave	0.39	0.47	0.39	0.52
Number of Unique Firms	461	473	1624	1637

Notes: This table presents the means of the matched sample of firms in the pre- and post-policy periods (2016-2017 and 2018-2019, respectively). Panel A presents employer ratings of employee performance, while Panel B presents employer ratings of the ease of coordination and of handling employee absences, on a scale of 1–10, with 1 being the most negative rating and 10 being the most positive rating. Panel C provides the proportion of firms with at least one employee using leave by gender and type of leave.

Panel B. As noted above, in addition to reporting standard errors clustered on the firm level, we also display Romano-Wolf *p*-values that adjust for multiple hypothesis testing (while also accounting for firm-level clustering). In Panel A, we find no statistically significant impacts on any of the five dimensions of employer ratings of employee performance, although the coefficients for employers' ratings of employee commitment and cooperation are positive and large in magnitude. In Panel B, we find 0.31 and 0.38 SD increases in these two ratings in the first year of the policy (with the former coefficient being marginally significant at the 10% level). The coefficients are reduced in magnitude and no longer statistically significant in the second year. Moreover, we note that for both of these outcomes, the coefficients in the pre-period are also positive, albeit insignificant.

Table 3 presents the analogous results for employer ratings of the ease of coordinating work schedules and dealing with employee absences of different durations. As with the outcomes in Table 2, we find no evidence of any adverse impacts. If anything, it appears that there are improvements in employers' ability to handle employee absences. Panel A, which presents results from our DD models, shows that the NY PFL policy leads to a 0.26 SD increase in employers' assessment of the ease of dealing with employee absences longer than 4 weeks. Consistent with the results on employer ratings of performance in Table 2, the event-study estimates in Panel B indicate that the improvement is concentrated in the first year of the policy. Specifically, in the first year of the policy, PFL is estimated to reduce the difficulty of dealing with absences of 4 weeks or more by 0.31 SD and of dealing with absences 2–4 weeks long by 0.37 SD. There is also a marginally significant improvement in the ease of coordinating work schedules in the first year.

Next, we analyze employee leave-taking variables in Table 4. While none of the coefficients is statistically significant in the DD models in Panel A, we do find that the effects on leave-taking materialize in the second year of the policy in the event-study models in

Table 2. DD and event-study estimates of NY paid family leave on employer ratings of employee performance.

	(1) Attendance	(2) Commitment	(3) Cooperation	(4) Productivity	(5) Teamwork
A. DD Models					
Post x NY	0.039	0.132	0.148	−0.017	0.007
	[0.094]	[0.096]	[0.100]	[0.099]	[0.100]
Romano-Wolf p-value	0.934	0.357	0.303	0.974	0.974
B. Event-Study Models					
2017xNY	−0.031	0.096	0.239	0.227	0.194
(pre-policy)	[0.134]	[0.141]	[0.138]	[0.140]	[0.146]
Romano-Wolf p-value	0.798	0.663	0.230	0.262	0.367
2018xNY	0.115	0.306*	0.378**	0.224	0.214
(post-policy)	[0.128]	[0.131]	[0.129]	[0.132]	[0.144]
Romano-Wolf p-value	0.339	0.060	0.012	0.186	0.206
2019xNY	−0.068	0.059	0.167	−0.024	0.001
(post-policy)	[0.126]	[0.137]	[0.146]	[0.142]	[0.151]
Romano-Wolf p-value	0.936	0.936	0.571	0.966	0.986
Firm/Year Observations	9186	9188	9192	9181	9170

Notes: All dependent variables are expressed as z−scores. Panel A reports the β3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 3. DD and event-study estimates of the effects of NY paid family leave on employer ratings of the ease of coordination and handling of employee absences.

	(1) Coordination	(2) Handling Absence < 2 Weeks	(3) Handling Absence 2–4 Weeks	(4) EHandling Absence > 4 Weeks
A. DD Models				
Post x NY	0.151	0.110	0.185	0.256**
	[0.115]	[0.104]	[0.102]	[0.100]
Romano-Wolf p-value	0.3194	0.319	0.1417	0.030
B. Event-Study Models				
2017xNY	0.143	0.054	0.007	−0.114
(pre-policy)	[0.131]	[0.136]	[0.139]	[0.147]
Romano-Wolf p-value	0.537	0.858	0.948	0.671
2018xNY	0.282*	0.198	0.366**	0.307**
(post-policy)	[0.146]	[0.132]	[0.129]	[0.135]
Romano-Wolf p-value	0.070	0.118	0.014	0.026
2019xNY	0.166	0.079	0.017	0.091
(post-policy)	[0.144]	[0.147]	[0.149]	[0.150]
Romano-Wolf p-value	0.513	0.814	0.912	0.814
Firm/Year Observations	9148	9117	9030	9047

Notes: All dependent variables are expressed as z−scores. Panel A reports the β3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Panel B. Specifically, we find a 19.5 percentage point (50 percent at the pre-policy mean) increase in the likelihood of any employee using any leave in the second year post-law. There is suggestive evidence that this impact is driven by increases in the likelihood of female employees taking parental leave, male employees taking parental leave, and male employees using leave to care for ill family members (although not all of these estimates are individually statistically significant once we account for multiple hypothesis testing).

In Table 5, we check whether the effects on employers' ratings of the ease of dealing with employee absences are heterogeneous across firms with and without any recent experience with workers taking leave by including an interaction with the indicator for whether a firm has any employee taking any leave in the past 12 months. While the results are not statistically significant once we account for multiple hypothesis testing, the large positive coefficients on the interaction terms suggest that the improvement in the ease of dealing with employee absences may be concentrated among firms that have had at least one employee take leave.

We explore heterogeneity in our findings by firm size in Appendix Tables A2 through A4. We split our sample into larger firms with 50 or more employees and smaller firms with 10–49 employees, reflecting FMLA eligibility for the former but not the latter subgroup. Interestingly, the increase in employee leave-taking occurs exclusively among the smaller firms, which is consistent with workers at these firms previously not having any access to government-provided job-protected leave. The impacts on employer ratings of employee performance and the ease of handling employee absences are

Table 4. DD and event-study estimates of the the effects of NY paid family leave on employee leave-taking.

	(1) Any Employee, Any Leave	(2) Female Employee – Parental	(3) Male Employee – Parental	(4) Female Employee – Serious Fam. Illness	(5) Male Employee – Serious Fam. Illness
A. DD Models					
Post x NY	0.062	0.041	0.029	−0.009	0.034
	[0.055]	[0.043]	[0.038]	[0.036]	[0.031]
Romano-Wolf *p*-value	0.623	0.635	0.635	0.761	0.623
B. Event-Study Models					
2017xNY	0.073	0.023	−0.010	0.047	0.066
(pre-policy)	[0.078]	[0.054]	[0.054]	[0.048]	[0.040]
Romano-Wolf *p*-value	0.649	0.882	0.882	0.649	0.289
2018xNY	0.002	0.003	−0.039	0.025	0.032
(post-policy)	[0.080]	[0.060]	[0.057]	[0.050]	[0.046]
Romano-Wolf *p*-value	1.000	1.000	0.938	0.938	0.938
2019xNY	0.195**	0.103	0.085	0.005	0.104**
(post-policy)	[0.081]	[0.057]	[0.046]	[0.054]	[0.042]
Romano-Wolf *p*-value	0.046	0.134	0.134	0.902	0.044
Pre-Policy Dept. Var. Mean	0.390	0.158	0.128	0.111	0.080
Firm/Year Observations	9226	9227	9227	9226	9227

Notes: Panel A reports the β3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

positive in both smaller and larger firms in our sample, with bigger point estimates for larger employers, although none of these effects is statistically significant due to small sample sizes.

Table 5. Differential effects of NY paid family leave on employer ratings of the ease of coordination and handling of employee absences, by whether firms have any leave takers.

	(1) Coordination	(2) Handling Absence < 2 Weeks	(3) Handling Absence 2–4 Weeks	(4) Handling Absence > 4 Weeks
Post x NY	0.023	−0.054	0.043	0.037
	[0.169]	[0.157]	[0.155]	[0.158]
Romano-Wolf p-value	0.976	0.972	0.976	0.976
Any Leave-Takers x Post x NY	0.320	0.395	0.353	0.547
	[0.271]	[0.280]	[0.274]	[0.276]
Romano-Wolf p-value	0.293	0.293	0.293	0.104
Firm/Year Observations	9147	9116	9029	9046

Notes: All dependent variables are expressed as z−scores. This table reports the β3 coefficients from estimating an augmented version of equation (1), which includes an indicator for whether a firm/year observation has at least one employee who has taken any leave in the past 12 months, as well as an interactions between this indicator and the NYs indicator, the Postt indicator, and the triple interaction with NYs × Postt. Models are estimated separately for each dependent variable. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

We next consider whether PFL may have affected the composition of firms. Because PFL might be disproportionately valued or used by part-time or female employees, and may impact employee retention, we report the results for the employee attributes (share part-time, share female, share who quit, and share who are absent without notice) from our DD and event-study models in Appendix Table A5. We do not see any statistically significant impacts on any of these variables in the DD models in Panel A. The event-study estimates indicate an 8.1 percentage point increase in the share of female employees in the first year of the policy, but it appears that this may reflect a pre-existing trend in this outcome (the coefficient is larger in magnitude in 2017, the year before NY PFL went into effect, although as noted our ability to assess pre-trends is limited with only two years of pre-law data). These results suggest that the previously discussed findings on employer ratings of employee performance and the ease of dealing with worker absences, and on employee leave-taking rates, are unlikely to be solely driven by changes in firm composition.

Discussion

Opposition to government-provided paid family leave in the United States largely rests on an argument that this policy will impose large burdens on businesses, especially small businesses. Accordingly, business community leaders, trade groups such as the National Federation of Independent Business, and the U.S. Chamber of Commerce have repeatedly expressed concerns with proposed PFL legislation. However, empirical evidence supporting these arguments has been lacking, largely due to data constraints.

We bring new data and empirical analysis to inform this discussion. We study New York's PFL program, which went into effect in 2018, and analyze outcomes among firms with 10—99 employees, using a survey that we conducted over a four-year period from 2016 to 2019. We match each NY firm with a PA firm on observable characteristics, and then estimate difference-in-differences models within matched pairs to compare changes in outcomes in NY firms from before to after the policy was implemented relative to changes in similar firms in PA during the same time period.

Our analysis does not provide evidence that New York's PFL policy has had adverse impacts on the employer outcomes measured in our survey. There are no statistically significant or economically meaningful adverse impacts on employer ratings of employee performance in terms of attendance, commitment, cooperation, productivity, and teamwork. In fact, employers' ratings of employee commitment and cooperation increase by 0.31 and 0.38 SD in the first year of the policy, respectively. We also find no indication that NY PFL has made it harder for employers to deal with workers' absences. Instead, we document 0.37 and 0.31 SD increases in employers' average rating of their ease of handling workers' absences two to four weeks and longer than four weeks in duration, respectively, in the first policy year. There are also positive point estimates for employers' ratings of the ease of coordinating work schedules and handling short (2 week) absences, although these are not statistically significant. It seems plausible that employers – who previously may have managed their employees' needs for extended time off on a case-by-case basis – find it easier to use a standardized state PFL program instead.

The findings suggest that the increases in employer ratings of employee commitment and cooperation, as well as their ease of handling workers' absences, may dissipate in the second year post-policy. We can only speculate, but a possible reason for this is that there is a large increase in the incidence of employee leave-taking in that year, particularly among firms with fewer than 50 employees, who would not have been previously eligible for FMLA leave. Thus, while employers could have found it easier to deal with long employee absences in the first year of the policy in which the number of such absences did not significantly increase, this beneficial effect might be reduced or eliminated as the amount of leave-taking increases (or as leave durations increase), necessitating further employer adjustment. That being said, we see no evidence of a deterioration in employer outcomes in the second year of the policy, even among the smallest employers in which the increase in leave-taking takes place. Thus, it appears that the establishment of rights to leave is valuable for workers in small firms, but does not have any detectable downside for their employers.

While our study delivers some of the first estimates of the causal impacts of PFL on employer outcomes, important questions remain. As noted above, the New York program gradually expanded in generosity through 2021, and more research is needed to shed light on how changes in program parameters influence employers. More generally, our data reflect a phase-in period when employers (and employees) were still finding out about the program. Further research, especially with very small firms, may be necessary to understand how employers learn about and implement state-level PFL programs. In addition, while our results suggest largely positive overall PFL effects on employers, over the period we examine, they also raise the possibility of less favorable trends along some dimensions in the longer-run effects of PFL programs on employers. Gathering further data and evaluating longer-term impacts on the outcomes considered here, and other key outcomes such as leave duration, are important directions for future research.

It is also important to note that in 2017, the year before NY PFL went into effect, New York state initiated a gradual minimum wage policy targeting a $15 minimum wage, with the exact schedule varying by region and firm size (NY Department of Labor, 2019). This policy may have also influenced employer outcomes, although it is unlikely to have had a direct impact on their ease of managing employee absences. That said, the initiation of the minimum wage policy may help explain the positive (but insignificant) 'pre-trend' coefficients for employer ratings of employee performance.[9]

Further, the COVID-19 pandemic has significantly disrupted business operations and underscored the importance of paid leave for workers who get sick, must take care of ill family members, or lack childcare due to closures of schools and daycares. Our most recent follow-up survey from fall 2020 provides more evidence on the implications of New York's PFL program for businesses during COVID-19 (Bartel et al., 2021).

Finally, our pre-PFL period only includes two years of data collection, which limits our ability to comprehensively assess outcome pre-trends. We also note that our matching algorithm selected only a subset of the Pennsylvania firms as suitable controls for the New York firms, indicating important differences in employer characteristics between the two states. As a growing number of states are planning to implement PFL programs in the coming years, researchers may consider collecting baseline data from other states for future analyses of PFL impacts on employer outcomes. This is particularly important as state policies now vary considerably along a number of relevant dimensions such as the length of leave, rate of pay, job protection, and eligibility requirements. NY's policy is more generous in terms of length of leave and rate of pay (but has a lower maximum weekly benefit) than the CA policy that was the subject of much of the previous research in this area, but other state policies such as WA are even more generous along some of these dimensions (Bartel et al., 2023). Further research is also needed to understand the extent to which results from one state are generalizable to another, in light of such policy differences and other institutional factors, as well as to understand which policy parameters are most consequential in terms of impacts on employers and employees.

Notes

1. In fact, business community leaders, trade groups such as the National Federation of Independent Business, and the U.S. Chamber of Commerce have repeatedly expressed concerns with proposed PFL legislation. See, for example: https://www.npr.org/sections/itsallpolitics/2015/07/15/422957640/lots-of-other-countries-mandate-paid-leave-why-not-the-us
2. Specifically, the ordinance requires that employers in San Francisco supplement the state-level PFL policy by providing workers with 100% wage replacement during leave.
3. Women who experience childbirth complications are eligible for longer leaves, with doctor certification. The maximum amount of leave under the TDI program is 26 weeks.
4. See: https://paidfamilyleave.ny.gov/employees for more details.
5. We also collected data from another neighboring state, New Jersey, which we hoped could serve as another pool of control firms. However, in the middle of our data collection, New Jersey substantially expanded its PFL program, making its firms unsuitable controls. NJ elected a new Democratic governor in 2018, who had promised to expand the PFL program. The expansion was signed into law in 2019.
6. For firms that had multiple employees take leave, we asked about the gender and reason for leave of the most recent leave-taker. We do not have information on employees who had children or had a family member with a serious illness but did not take any leave
7. We exclude these firm-level baseline controls when analyzing employee characteristics (share of employees who: are female, work part-time, quit in the past year, and were absent without notice in the past month) as outcomes. We also find that our results for other outcomes are similar if we exclude these controls (results available upon request).
8. The Romano-Wolf correction controls for the familywise error rate, which is the probability of rejecting at least one true null hypothesis among a family of hypotheses under a test. We treat each set of outcomes in each table panel as a family. (See Clarke et al., 2020; Romano et al., 2010; Romano & Wolf, 2005, 2016)
9. We do not have information on employee wages in our data, preventing us from directly analyzing firms with employees who were likely affected by the minimum wage policy. However, we have examined heterogeneity across firms in industries with more and fewer minimum wage workers based on information from the American Community Survey data, finding no evidence that these firms were differentially affected by NY PFL.

Acknowledgements

We thank Junying Fang and Jett Pettus for excellent research assistance. We thank participants at APPAM and AEA conferences for helpful feedback. We gratefully acknowledge funding for this research from Pivotal Ventures, Washington Center for Equitable Growth, Russell Sage Foundation, and Ford Foundation, and support from the Columbia Population Research Center which is funded by the National Institute for Child Health and Human Development (NICHD) through grant P2CHD058486.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

This work was supported by National Institute of Child Health and Human Development: [5P2CHD058486-14]; Pivotal Ventures; and the Washington Center for Equitable Growth.

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Appendices

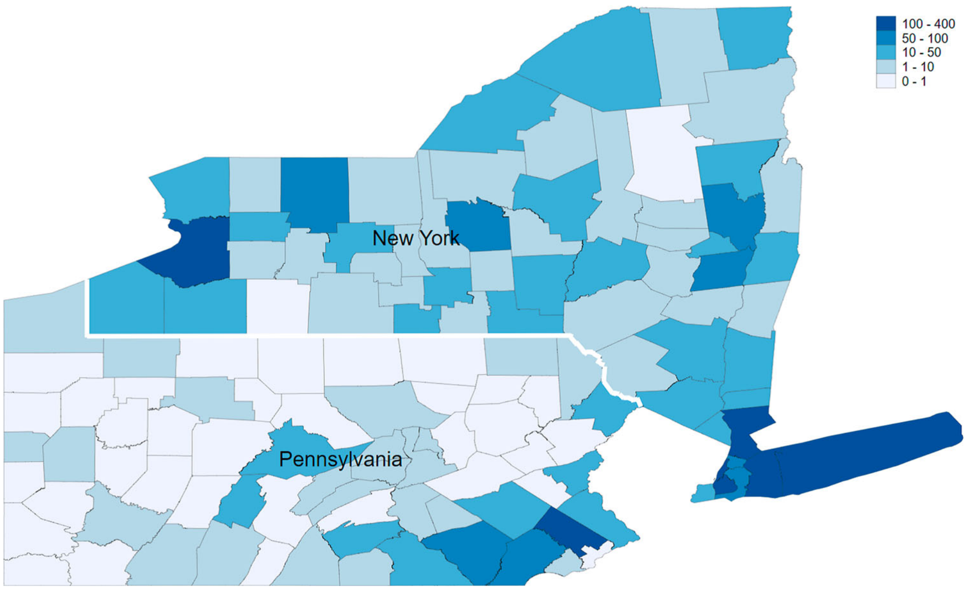

Figure A1. NY and PA Counties with Firms in the Matched Pair Sample.

Table A1. Pre- and post-match variable means, NY and PA firms, 2016–2019.

	All Firms		Matched Firms		Pre-Match Diff.	Post-Match Diff.
	NY	PA	NY	PA		
County Unemployment Rate, 2016	4.593	5.575	4.593	4.748	−0.981	−0.154
County Average Weekly Wage, 2016	1200.34	1025.37	1200.34	1063.47	174.964	136.860
Number of Employees at Baseline	36.680	36.002	36.680	36.281	0.678	0.407
Number Unique Firms	2364	2198	2364	655		

Notes: The first two columns report means for all NY and PA firms in our data, respectively. The next two columns report means for NY and PA firms in the matched-pair sample, respectively. The second-to-last column ('Pre-Match Diff.') reports the difference between mean characteristics in NY and PA firms before the match. The last column ('Post-Match Diff.') provides the mean within-matched-pair difference. County-level characteristics are from the 2016 Quarterly Census of Employment and Wages. Firms are also matched on exact NAICS industry code and an indicator for whether the firm is in a metro area.

Table A2. DD estimates of the effects of NY paid family leave on employer ratings of employee performance and ease of coordination and handling of absences, by firm size.

A. Employer Ratings of Employee Performance

	(1) Attendance	(2) Commitment	(3) Cooperation	(4) Productivity	(5) Teamwork
Firms with 50–99 Employees					
Post x NY	−0.139	0.139	0.049	0.000	0.030
	[0.166]	[0.169]	[0.186]	[0.166]	[0.180]
Romano-Wolf p-value	0.816	0.816	0.990	1.000	0.990
Firm/Year Observations	3103	3100	3102	3096	3102
Firms with 10–49 Employees					
Post x NY	0.153	0.111	0.191	−0.032	−0.025
	[0.121]	[0.124]	[0.121]	[0.130]	[0.124]
Romano-Wolf p-value	0.467	0.641	0.335	0.938	0.938
Firm/Year Observations	6083	6088	6090	6085	6068

B. Employer Ratings of Ease of Coordination and of Handling Absenses

	(1) Coordination	(2) Ease of Handling Absence < 2 Weeks	(3) Ease of Handling Absence 2–4 Weeks	(4) Ease of Handling Absence > 4 Weeks
Firms with 50–99 Employees				
Post x NY	0.194	0.123	0.324	0.421*
	[0.170]	[0.162]	[0.170]	[0.184]
Romano-Wolf p-value	0.419	0.423	0.138	0.060
Firm/Year Observations	3078	3054	3036	3024
Firms with 10–49 Employees				
Post x NY	0.087	0.053	0.053	0.132
	[0.152]	[0.137]	[0.132]	[0.123]
Romano-Wolf p-value	0.870	0.870	0.870	0.591
Firm/Year Observations	6070	6063	5994	6023

Notes: All dependent variables are expressed as z−scores. The table reports the β3 coefficients from equation (1), separately for each dependent variable, and for each sub-sample. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A3. DD estimates of the effects of NY paid family leave on employee leave-taking, by firm size.

	(1) Any Employee on Leave	(2) Female Employee – Parental	(3) Male Employee – Parental	(4) Female Employee – Serious Fam. Illness	(5) Male Employee – Serious Fam. Illness
Firms with 50–99 Employees					
Post x NY	−0.078	−0.012	−0.019	−0.048	−0.021
	[0.086]	[0.083]	[0.072]	[0.059]	[0.061]
Romano-Wolf p-value	0.844	0.980	0.980	0.878	0.980
Pre-Policy Dep. Var. Mean	0.434	0.215	0.140	0.116	0.101
Firm/Year Observations	3113	3114	3114	3113	3114
Firms with 10–49 Employees					
Post x NY	0.148	0.075	0.061	0.010	0.061
	[0.074]	[0.051]	[0.047]	[0.047]	[0.037]
Romano-Wolf p-value	0.166	0.333	0.333	0.814	0.283
Pre-Policy Dep. Var. Mean	0.366	0.127	0.122	0.109	0.068
Firm/Year Observations	6113	6113	6113	6113	6113

Notes: The table reports the β3 coefficients from equation (1), separately for each dependent variable, and for each subsample. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A4. DD estimates of the effects of NY paid family leave on employee attributes, by firm size.

	(1) Share Part-Time	(2) Share Female	(3) Share Quit	(4) Share Absent Without Notice
Firms with 50–99 Employees				
Post x NY	0.028	0.016	−0.013	0.026
	[0.036]	[0.033]	[0.022]	[0.014]
Romano-Wolf p-value	0.699	0.731	0.731	0.140
Pre-Policy Dept. Var. Mean	0.282	0.485	0.167	0.069
Firm/Year Observations	3391	3393	3261	3157
Firms with 10–49 Employees				
Post x NY	0.007	0.003	0.015	0.011
	[0.032]	[0.037]	[0.038]	[0.020]
Romano-Wolf p-value	0.970	0.970	0.970	0.952
Pre-Policy Dept. Var. Mean	0.301	0.445	0.209	0.098
Firm/Year Observations	6367	6357	6271	6200

Notes: The table reports the β3 coefficients from equation (1), separately for each dependent variable, and for each subsample. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table A5. DD and event-study estimates of the effects of NY paid family leave on employee attributes.

	(1) Share Part-Time	(2) Share Female	(3) Share Quit	(4) Share Absent Without Notice
A. DD Models				
Post x NY	0.014	0.007	0.003	0.017
	[0.023]	[0.026]	[0.024]	[0.013]
Romano-Wolf p-value	0.864	0.944	0.944	0.445
B. Event-Study Models				
2017xNY	0.027	0.120***	−0.005	−0.023
(pre-policy)	[0.029]	[0.029]	[0.044]	[0.017]
Romano-Wolf p-value	0.527	0.002	0.914	0.409
2018xNY	0.035	0.081**	0.009	0.005
(post-policy)	[0.029]	[0.030]	[0.033]	[0.017]
Romano-Wolf p-value	0.471	0.024	0.942	0.942
2019xNY	0.022	0.059	−0.007	0.006
(post-policy)	[0.031]	[0.039]	[0.037]	[0.018]
Romano-Wolf p-value	0.822	0.383	0.912	0.912
Pre-Policy Dept. Var. Mean	0.294	0.459	0.194	0.088
Firm/Year Observations	9758	9750	9532	9357

Notes: Panel A reports the β3 coefficients from equation (1), while Panel B reports the coefficients from the event-study version of equation (1), separately for each dependent variable. Standard errors clustered on the firm level are in brackets, while Romano-Wolf *p*-values adjusted for multiple hypothesis testing are reported in the rows below the standard errors. Significance levels (based on Romano-Wolf *p*-values): * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.